1. PREDICTING HOUSE PRICES

EX.N0 : 1	**Predicting House Prices**
DATE : 24/07/2024	

PROBLEM STATEMENT: Build a regression model to predict house prices based on features like location, size, and amenities.

PYTHON CONCEPTS: Functions, classes, numeric types, sequences.

VISUALIZATION: Plotting regression line, residual plots.

MULTIVARIATE ANALYSIS: Multiple regression.

DATASET: Kaggle House Prices

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

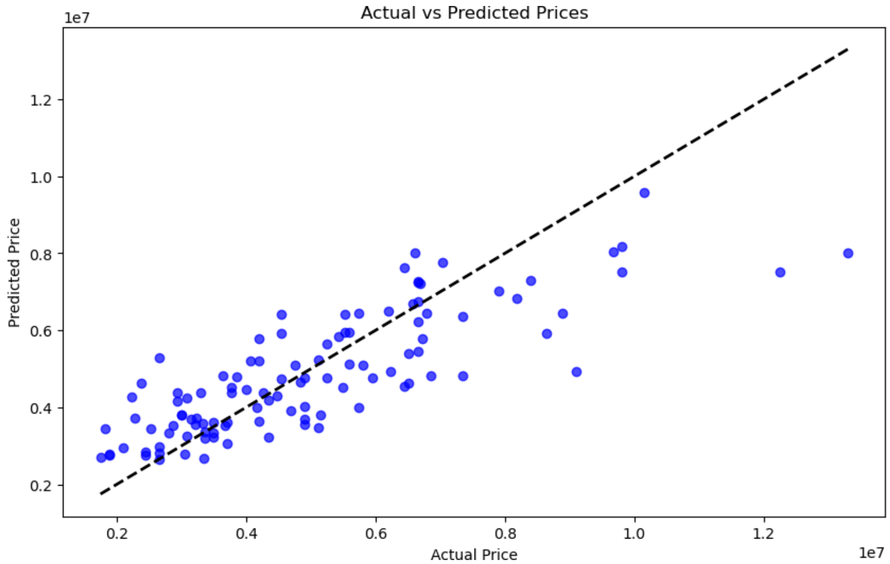
PROGRAM:

```
import pandas as pd

from sklearn.preprocessing import LabelEncoder

from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LinearRegression

from sklearn.metrics import r2_score, mean_absolute_error

import matplotlib.pyplot as plt

file_path = 'C:/Users/APPU/Downloads/Housing.csv'

housing_data = pd.read_csv(file_path)

categorical_features = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
'prefarea', 'furnishingstatus']

le = LabelEncoder()

for feature in categorical_features:

housing_data[feature] = le.fit_transform(housing_data[feature])

X = housing_data.drop('price', axis=1)y = housing_data['price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

r2 = r2_score(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred, alpha=0.7, color='b')

plt.plot([y_test.min(), y_test.max()],

[y_test.min(), y_test.max()], 'k--', lw=2)

plt.xlabel('Actual Price')

plt.ylabel('Predicted Price')

plt.title('Actual vs Predicted Prices')

plt.show()
```

print(f'R-squared (R²): {r2}')

print(f'Mean Absolute Error (MAE): {mae}')




```
import numpy as np
test=np.array([ 7420,4,2,3,1,0,0,0,1,2,1,0]).reshape(-12,12)
model.predict(test)
```

```
array([8004072.41154001])
```

<u>RESULT</u>:

Thus, the program for house price prediction is executed successfully.

2. CUSTOMER SEGMENTATION FOR AN E-COMMERCE COMPANY

EX.N0 : 2	**Customer Segmentation for an E-commerce Company**
DATE : 05/08/2024	

PROBLEM STATEMENT: Perform cluster analysis to segment customers based on purchasing behaviour.

PYTHON CONCEPTS: Data structures, file reading/writing.

VISUALIZATION: Cluster plots.

MULTIVARIATE ANALYSIS: Cluster analysis with k-means, hierarchical clustering.

DATASET: Online Retail Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

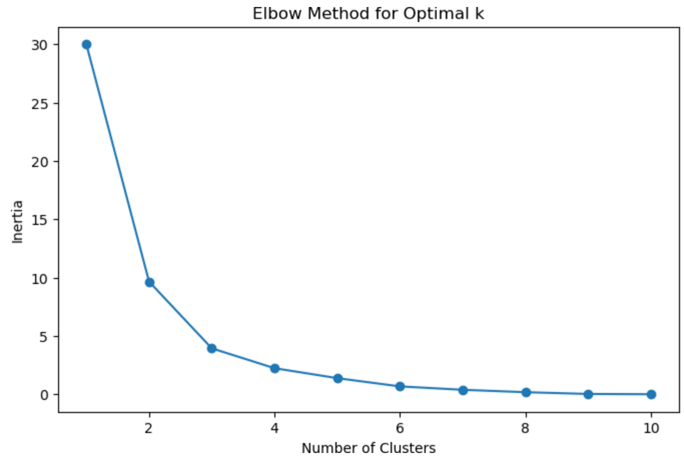
Step 6: Print equal metric & test the cell.

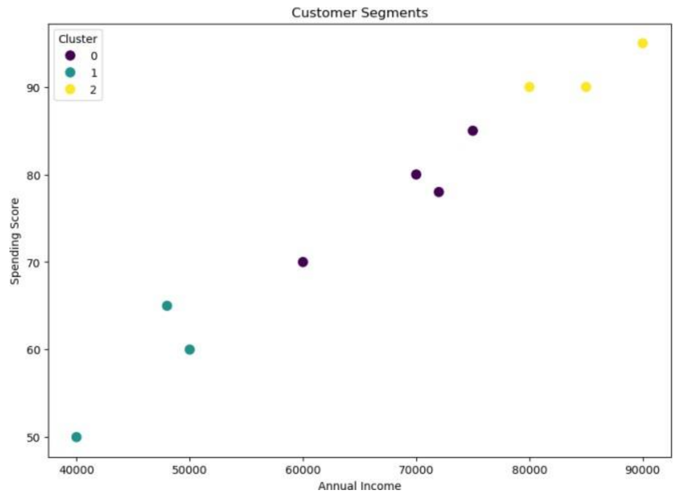
PROGRAM:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

```
os.environ['OMP_NUM_THREADS'] = '1'
data = {'CustomerID': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
'Age': [25, 45, 35, 50, 23, 33, 43, 36, 29, 55],
'AnnualIncome': [50000, 60000, 70000, 80000, 40000, 75000, 85000, 72000, 48000, 90000],
'SpendingScore': [60, 70, 80, 90, 50, 85, 90, 78, 65, 95] }
df = pd.DataFrame(data)
features = df[['Age', 'AnnualIncome', 'SpendingScore']]
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features) inertia = []
k_range = range(1, 11) for k in k_range:
kmeans = KMeans(n_clusters=k, n_init=10, random_state=0)
kmeans.fit(scaled_features)
inertia.append(kmeans.inertia_) plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.xlabel('Number of Clusters') plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k') plt.show() optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, n_init=10, random_state=0)
df['Cluster'] = kmeans.fit_predict(scaled_features)
plt.figure(figsize=(10, 7))
sns.scatterplot(data=df, x='AnnualIncome', y='SpendingScore', hue='Cluster', palette='viridis',
s=100)
plt.title('Customer Segments')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend(title='Cluster')
plt.show()
print(df)
```

OUTPUT:





	CustomerID	Age	AnnualIncome	SpendingScore	Cluster
0	1	25	50000	60	1
1	2	45	60000	70	0
2	3	35	70000	80	0
3	4	50	80000	90	2
4	5	23	40000	50	1
5	6	33	75000	85	0
6	7	43	85000	90	2
7	8	36	72000	78	0
8	9	29	48000	65	1
9	10	55	90000	95	2

RESULT:

Thus, the program for Customer Segmentation for an E-commerce Company is executed successfully.

3. SENTIMENT ANALYSIS OF MOVIE REVIEWS

EX.N0 : 3	**SENTIMENT ANALYSIS OF MOVIE REVIEWS**
DATE : 07/08/2024	

PROBLEM STATEMENT: Classify movie reviews as positive or negative using text Data.

PYTHON CONCEPTS: Text files, sequences, flow controls.

VISUALIZATION: Word cloud, bar plots.

MULTIVARIATE ANALYSIS: PCA for text data, logistic regression.

DATASET: IMDB Movie Reviews.

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

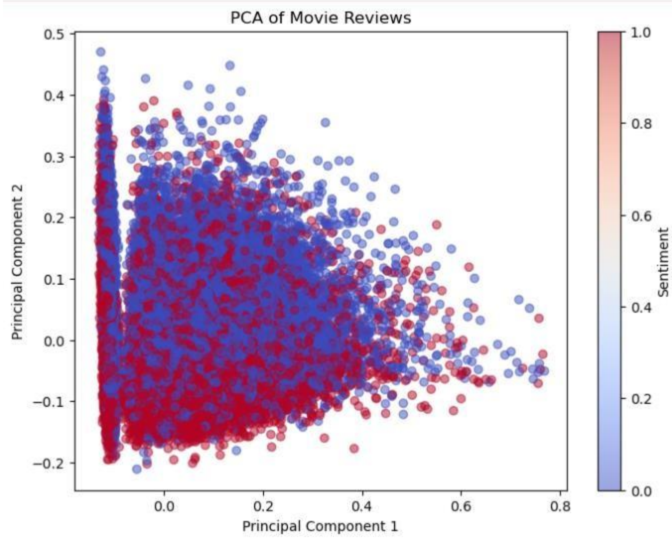
PROGRAM:

```
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
import seaborn as sns
nltk.download('punkt')
nltk.download('stopwords')
df = pd.read_csv('C:/Users/AI_LAB/Downloads/IMDB Dataset.csv')
stop_words = set(stopwords.words('english'))
stemmer = PorterStemmer()
def preprocess_text(text):
tokens = word_tokenize(text.lower())
tokens = [stemmer.stem(word) for word in tokens if word.isalpha() and word not in stop_words]
return ' '.join(tokens)
df['cleaned_review'] = df['review'].apply(preprocess_text)
vectorizer = TfidfVectorizer(max_features=5000)
X = vectorizer.fit_transform(df['cleaned_review']).toarray()
encoder = LabelEncoder()
y = encoder.fit_transform(df['sentiment'])
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='coolwarm', alpha=0.5)
plt.title('PCA of Movie Reviews')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Sentiment')
plt.show()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
positive_reviews = ' '.join(df[df['sentiment'] == 1]['cleaned_review'])
negative_reviews = ' '.join(df[df['sentiment'] == 0]['cleaned_review'])
plt.figure(figsize=(12, 6))
if len(positive_reviews.strip()) > 0:
plt.subplot(1, 2, 1)
plt.imshow(WordCloud(width=800, height=400,
background_color='white').generate(positive_reviews), interpolation='bilinear')
plt.title('Positive Reviews')
plt.axis('off')
else: print("No content available for positive reviews.")
if len(negative_reviews.strip()) > 0:
plt.subplot(1, 2, 2)
plt.imshow(WordCloud(width=800, height=400,
background_color='white').generate(negative_reviews), interpolation='bilinear')
plt.title('Negative Reviews')
plt.axis('off') else:
print("No content available for negative reviews.")
plt.show()
sns.countplot(x='sentiment', data=df)
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()
```

OUTPUT:




```
Confusion Matrix:
[[4306  655]
 [ 511 4528]]

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.87      0.88      4961
           1       0.87      0.90      0.89      5039

    accuracy                           0.88     10000
   macro avg       0.88      0.88      0.88     10000
weighted avg       0.88      0.88      0.88     10000
```

RESULT:

Thus, the program for sentiment analysis of movie reviews is executed successfully.

<u>4. STOCK MARKET ANALYSIS</u>

EX.N0 : 4	**STOCK MARKET ANALYSIS**
DATE : 14/08/2024	

PROBLEM STATEMENT: Analyse stock market data to predict future stock prices.

PYTHON CONCEPTS: Data structures, file reading/writing, functions.

VISUALIZATION: Line plots, candlestick charts.

MULTIVARIATE ANALYSIS: Time series analysis, regression.

DATASET: Yahoo Finance Stock Data.

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

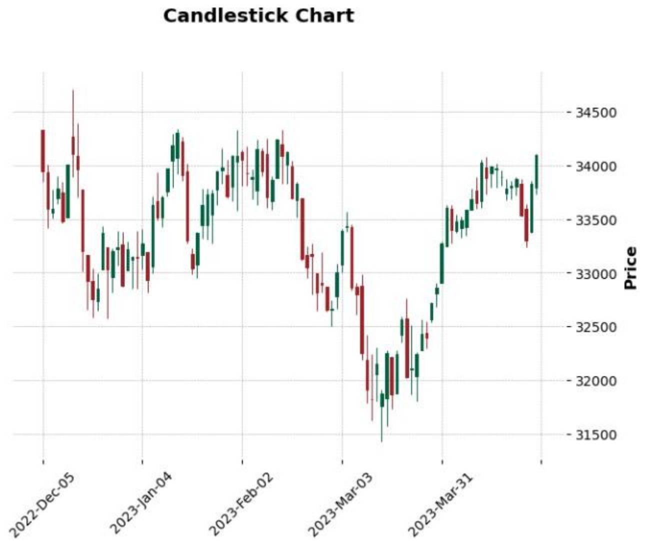
Step 6: Print equal metric & test the cell.

PROGRAM:

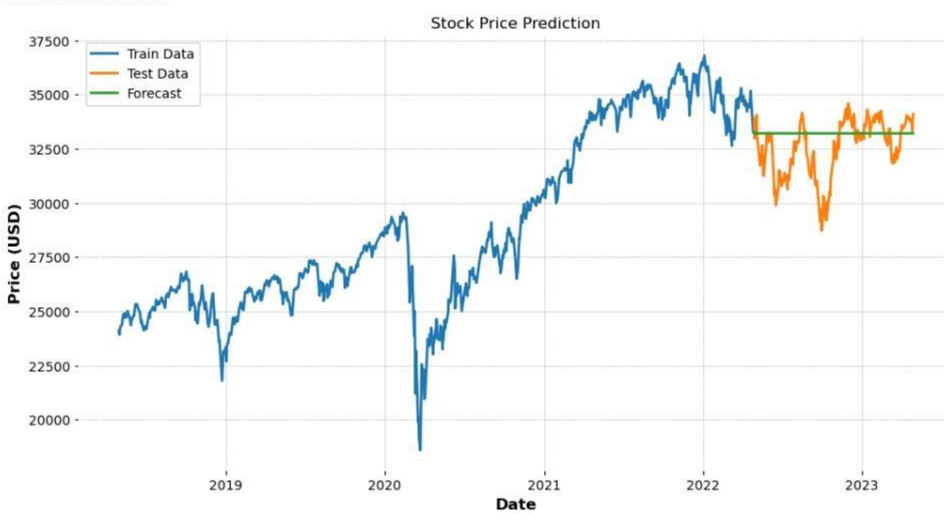
```
import pandas as pd
import matplotlib.pyplot as plt
import mplfinance as mpf
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
import numpy as np
```

```
file_path = r'C:\Users\APPU\Downloads\yahoo_data.xlsx'
data = pd.read_excel(file_path, index_col='Date', parse_dates=True)
data.rename(columns={'Close*': 'Close', 'Adj Close**': 'Adj Close'}, inplace=True)
data.sort_index(inplace=True)
data.ffill(inplace=True)
if 'Adj Close' in data.columns:
plt.figure(figsize=(12, 6))
plt.plot(data['Adj Close'], label='Adjusted Close Price')
plt.title('Adjusted Close Price Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()
reduced_data = data[-100:] # Reduce data points for candlestick chart
mpf.plot(reduced_data, type='candle', style='charles', title='Candlestick Chart')
train_data, test_data = data['Adj Close'][:int(len(data)*0.8)], data['Adj Close'][int(len(data)*0.8):]
model = ARIMA(train_data, order=(5, 1, 0))
model_fit = model.fit()
forecast = model_fit.forecast(steps=len(test_data))
mse = mean_squared_error(test_data, forecast)
rmse = np.sqrt(mse)
print(f'RMSE: {rmse}')
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data, label='Train Data')
plt.plot(test_data.index, test_data, label='Test Data')
plt.plot(test_data.index, forecast, label='Forecast')
plt.title('Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()
```

OUTPUT:



RMSE: 1517.2016308018185



RESULT:

Thus, the program for stock market analysis is executed successfully.

5. LOAN DEFAULT PREDICTION

EX.N0 : 5	**LOAN DEFAULT PREDICTION**
DATE : 21/08/2024	

PROBLEM STATEMENT: Predict loan default probability based on borrower information.

PYTHON CONCEPTS: Classes, functions, sequences.

VISUALIZATION: ROC curve, bar plots.

MULTIVARIATE ANALYSIS: Logistic regression, factor analysis.

DATASET: Lending Club Loan Data

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

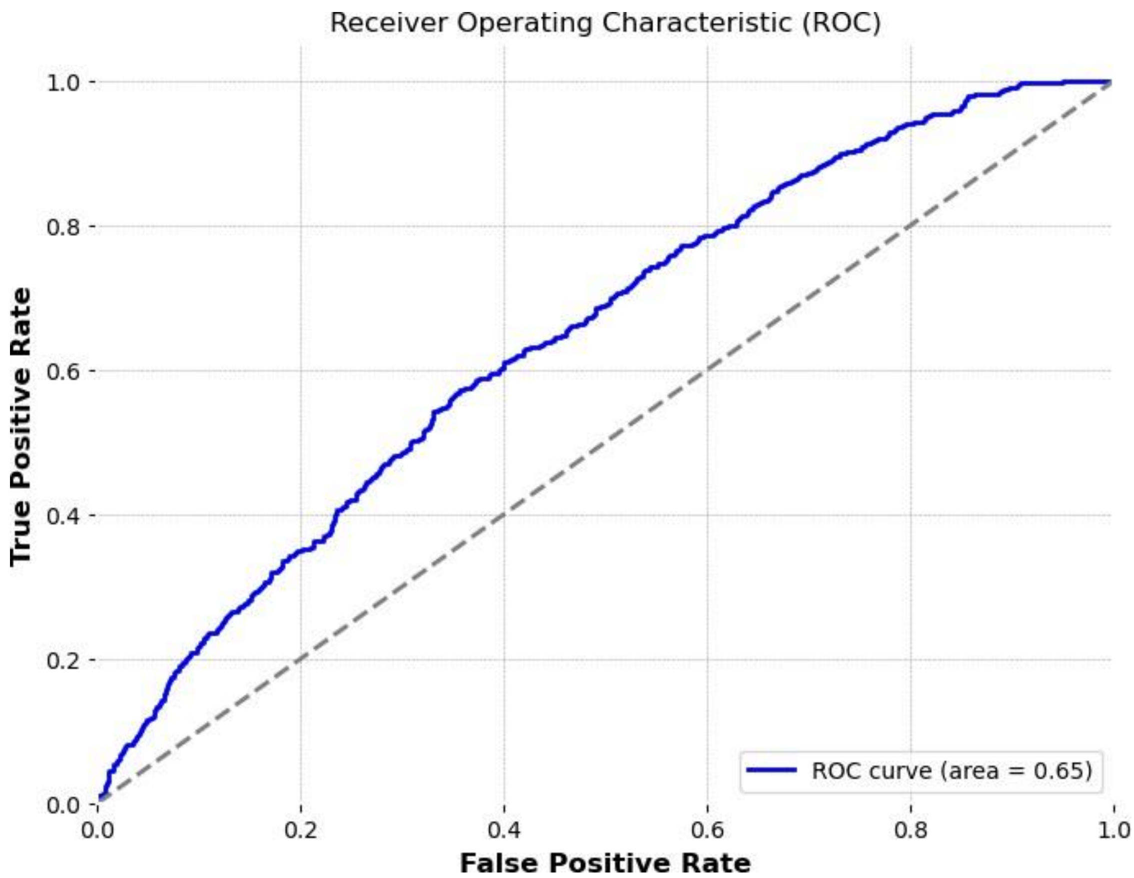
Step 6: Print equal metric & test the cell.

PROGRAM:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import os
```

```
file_path = 'C:/Users/APPU/Downloads/loan_data.csv'  # Update path accordingly
if os.path.exists(file_path):
df =  pd.read_csv(file_path)
print("Data loaded successfully.") else:
print(f"File not found: {file_path}")
dummies = pd.get_dummies(df['purpose'], drop_first=True)
df = pd.concat([df, dummies], axis=1)
df.drop('purpose', inplace=True, axis=1)
X = df.drop(['not.fully.paid'], axis=1)
y = df['not.fully.paid']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.33, random_state=42)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred_prob = model.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()
```

OUTPUT:



RESULT:

Thus, the program for loan default prediction is executed successfully.

6. IMAGE CLASSIFICATION

EX.N0 : 6	IMAGE CLASSIFICATION
DATE : 04/09/2024	

PROBLEM STATEMENT: Classify images into categories using various features.

PYTHON CONCEPTS: File handling, classes.

VISUALIZATION: Image plots, feature importance plots.

MULTIVARIATE ANALYSIS: PCA, clustering.

DATASET: CIFAR-10 Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

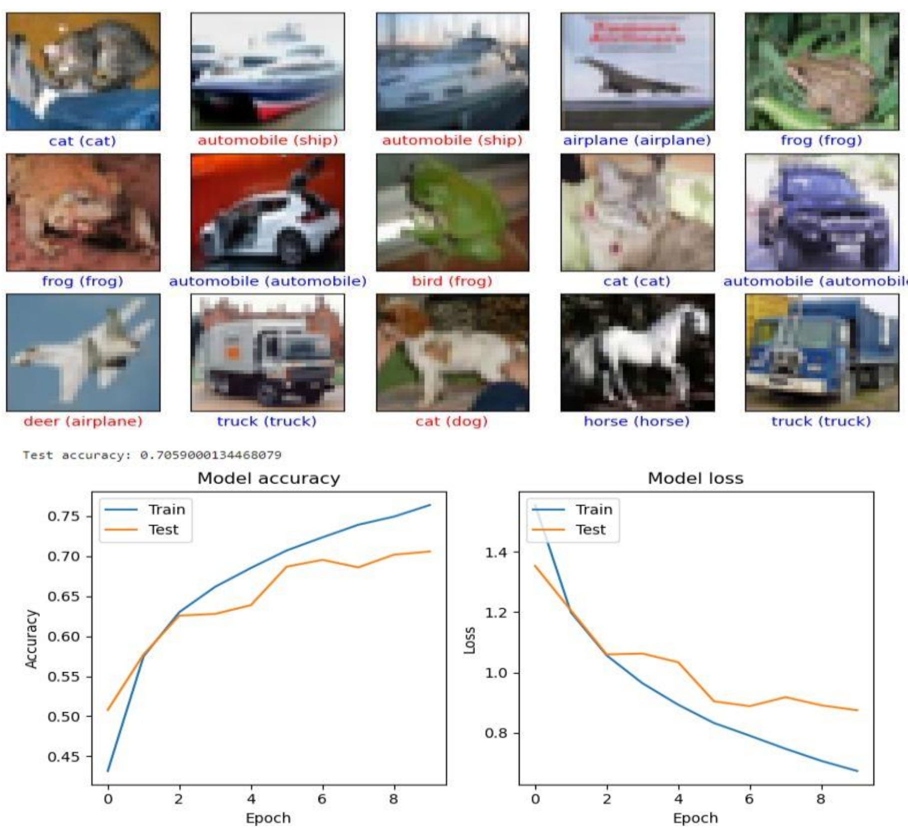
PROGRAM:

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import numpy as np
```

```
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.cifar10.load_data()
X_train, X_test = X_train / 255.0, X_test / 255.0
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
'dog', 'frog', 'horse', 'ship', 'truck']
plt.figure(figsize=(10,10))
for i in range(25): plt.subplot(5,5,i+1)
plt.xticks([]) plt.yticks([]) plt.grid(False)
plt.imshow(X_train[i], cmap=plt.cm.binary)
plt.xlabel(class_names[y_train[i][0]])
plt.show() model = models.Sequential([
layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.Flatten(), layers.Dense(64, activation='relu'),
layers.Dense(10)  ]) model.compile(optimizer='adam',
loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10,
validation_data=(X_test, y_test))
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=2)
print(f"\nTest accuracy: {test_acc}")
plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1) plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy') plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.subplot(1, 2, 2) plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss') plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.tight_layout() plt.show()
```

```
predictions = model.predict(X_test)
plt.figure(figsize=(10, 10))
for i in range(25): plt.subplot(5, 5, i+1)
plt.xticks([]) plt.yticks([]) plt.grid(False)
plt.imshow(X_test[i], cmap=plt.cm.binary)
predicted_label = np.argmax(predictions[i])
true_label = y_test[i][0]
color = 'blue' if predicted_label == true_label else 'red'
plt.xlabel(f"{class_names[predicted_label]} ({class_names[true_label]})", color=color)
plt.show()
```

OUTPUT:



RESULT:

Thus, the program for Image Classification is executed successfully.

7. PREDICTING DIABETES

EX.N0 : 7	PREDICTING DIABETES
DATE : 11/09/2024	

PROBLEM STATEMENT: Predict the onset of diabetes based on medical measurements.

PYTHON CONCEPTS: Data structures, numeric types, functions.

VISUALIZATION: Scatter plots, heatmaps.

MULTIVARIATE ANALYSIS: Logistic regression, LDA.

DATASET: Pima Indians Diabetes Database

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

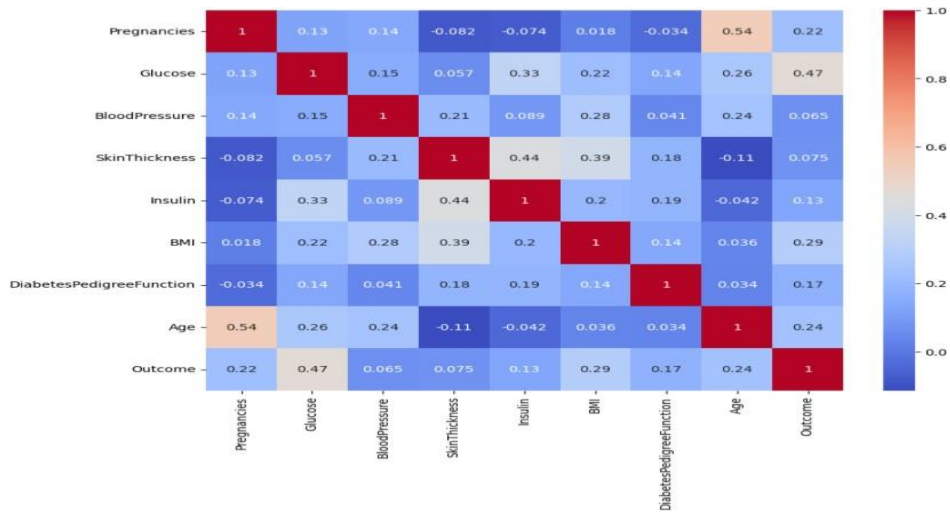
PROGRAM:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
url = https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv
columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI',
'DiabetesPedigreeFunction', 'Age', 'Outcome']
```

```
data = pd.read_csv(url, header=None, names=columns)
print("First 5 records:\n", data.head())
print("\nStatistical Summary:\n", data.describe())
print("\nDataset Info:\n")
print(data.info())
sns.pairplot(data, hue='Outcome')
plt.show()
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
X = data.drop('Outcome', axis=1)
y = data['Outcome']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
accuracy = accuracy_score(y_test, y_pred)
print(f"\nModel Accuracy: {accuracy * 100:.2f}%")
sample = X_test.iloc[0].values.reshape(1, -1)
sample_prediction = model.predict(sample)
print(f"\nPrediction for sample case (1 = Diabetes, 0 = No Diabetes): {sample_prediction[0]}")
```

OUTPUT:

```
First 5 records:
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1
```



```
Confusion Matrix:
[[120  31]
 [ 30  50]]

Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.79      0.80       151
           1       0.62      0.62      0.62        80

    accuracy                           0.74       231
   macro avg       0.71      0.71      0.71       231
weighted avg       0.74      0.74      0.74       231


Model Accuracy: 73.59%

Prediction for sample case (1 = Diabetes, 0 = No Diabetes): 0
```

RESULT:

Thus, the program for predicting diabetes is executed successfully.

8. WINE QUALITY PREDICTION

EX.N0 : 8	WINE QUALITY PREDICTION
DATE : 18/09/2024	

PROBLEM STATEMENT: Predict the quality of wine based on various chemical properties.

PYTHON CONCEPTS: Classes, sequences, file handling.

VISUALIZATION: Histograms, box plots.

MULTIVARIATE ANALYSIS: Multiple regression, factor analysis.

DATASET: Wine Quality Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

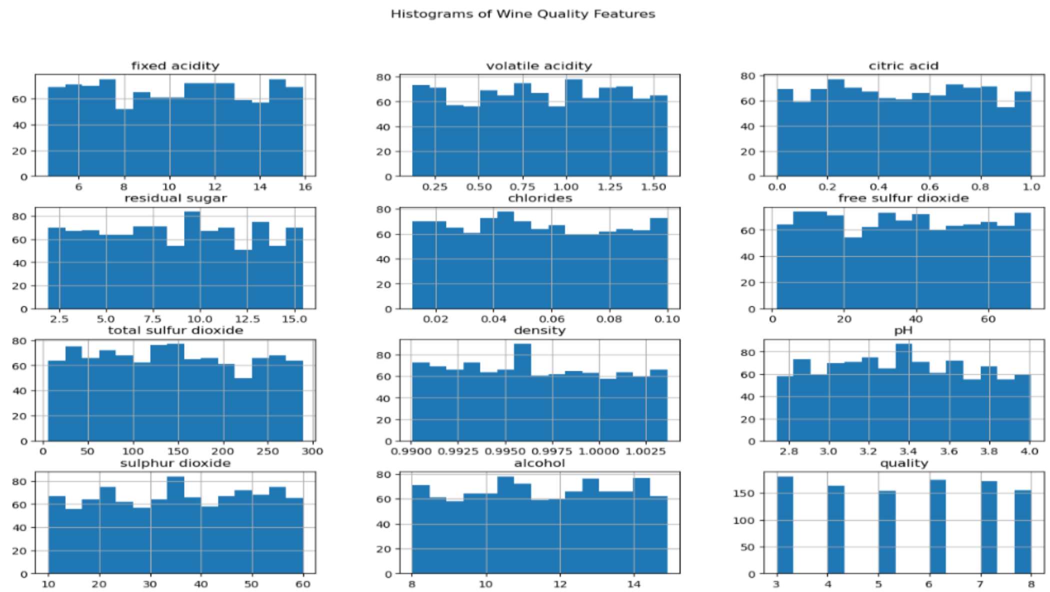
PROGRAM:

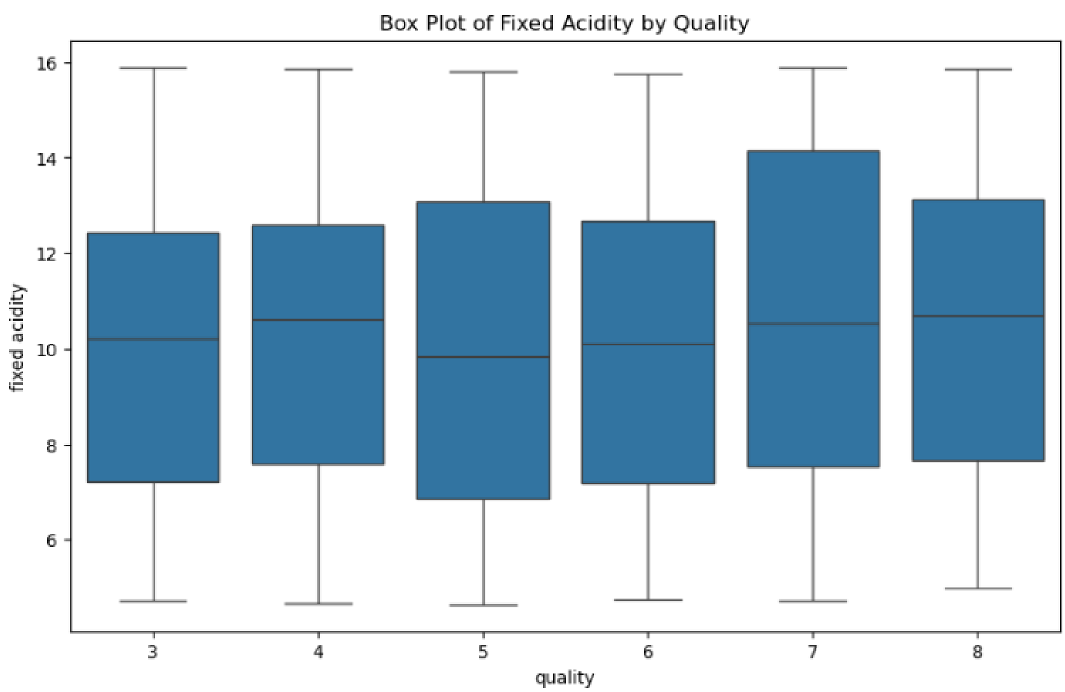
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
from sklearn.metrics import mean_squared_error, r2_score
class WineQualityPredictor:
def___init_(self, num_samples=1000):
self.num_samples = num_samples
self.data = None
self.model = None
def generate_data(self):
np.random.seed(42)
quality = np.random.randint(3, 9, self.num_samples)  # Quality scores between 3 and 8
fixed_acidity = np.random.uniform(4.6, 15.9, self.num_samples)
volatile_acidity = np.random.uniform(0.12, 1.58, self.num_samples)
citric_acid = np.random.uniform(0, 1, self.num_samples)
residual_sugar = np.random.uniform(1.9, 15.5, self.num_samples)
chlorides = np.random.uniform(0.012, 0.1, self.num_samples)
free_sulfur_dioxide = np.random.uniform(1, 72, self.num_samples)
total_sulfur_dioxide = np.random.uniform(6, 289, self.num_samples)
density = np.random.uniform(0.99007, 1.00369, self.num_samples)
pH = np.random.uniform(2.74, 4.01, self.num_samples)
sulfur_dioxide = np.random.uniform(10, 60, self.num_samples)
alcohol = np.random.uniform(8.0, 14.9, self.num_samples)
self.data = pd.DataFrame({
'fixed acidity': fixed_acidity, 'volatile acidity': volatile_acidity, 'citric acid': citric_acid,
'residual sugar': residual_sugar, 'chlorides': chlorides, 'free sulfur dioxide': free_sulfur_dioxide,
'total sulfur dioxide': total_sulfur_dioxide, 'density': density, 'pH': pH,
'sulphur dioxide': sulfur_dioxide, 'alcohol': alcohol, 'quality': quality })
print(f"Synthetic Data Generated: {self.data.shape[0]} rows and {self.data.shape[1]} columns")
def visualize_data(self):
self.data.hist(bins=15, figsize=(15, 10))
plt.suptitle('Histograms of Wine Quality Features')
plt.show() plt.figure(figsize=(10, 6))
sns.boxplot(x='quality', y='fixed acidity', data=self.data)
plt.title('Box Plot of Fixed Acidity by Quality')
plt.show() def preprocess_data(self):
X = self.data.drop('quality', axis=1)
y = self.data['quality']
```

```
return X, y def train_model(self, X, y):
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
self.model = LinearRegression()
self.model.fit(X_train, y_train)
y_pred = self.model.predict(X_test)
return y_train, y_test, y_pred
def evaluate_model(self, y_test, y_pred):
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f'Mean Squared Error: {mse}') print(f'R^2 Score: {r2}')
def predict_quality(self, input_features):
input_df = pd.DataFrame([input_features], columns=self.data.columns[:-1])
prediction = self.model.predict(input_df) return prediction[0]
def run(self): self.generate_data() self.visualize_data()
X, y = self.preprocess_data()
y_train, y_test, y_pred = self.train_model(X, y)
self.evaluate_model(y_test, y_pred)
if___name___== "__main__":
wine_predictor = WineQualityPredictor(num_samples=1000)
wine_predictor.run()
example_features = {
'fixed acidity': 7.4, 'volatile acidity': 0.7, 'citric acid': 0.0,
'residual sugar': 1.9, 'chlorides': 0.076, 'free sulfur dioxide': 11.0,
'total sulfur dioxide': 34.0, 'density': 0.9978, 'pH': 3.51,
'sulphur dioxide': 45.0, 'alcohol': 9.4 }
predicted_quality = wine_predictor.predict_quality(example_features)
print(f'Predicted Wine Quality: {predicted_quality:.2f}')
```

OUTPUT:






```
Mean Squared Error: 2.8525212491984275
R^2 Score: -0.0010251435985495494
Predicted Wine Quality: 5.51
```

RESULT:

Thus, the program for wine quality prediction is executed successfully.

9. HEART DISEASE PREDICTION

EX.N0 : 9	HEART DISEASE PREDICTION
DATE : 07/10/2024	

PROBLEM STATEMENT: Predict heart disease based on clinical parameters

PYTHON CONCEPTS: Functions, data structures.

VISUALIZATION: Pair plots, ROC curve.

MULTIVARIATE ANALYSIS: Logistic regression, PCA.

DATASET: Heart Disease Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

PROGRAM:

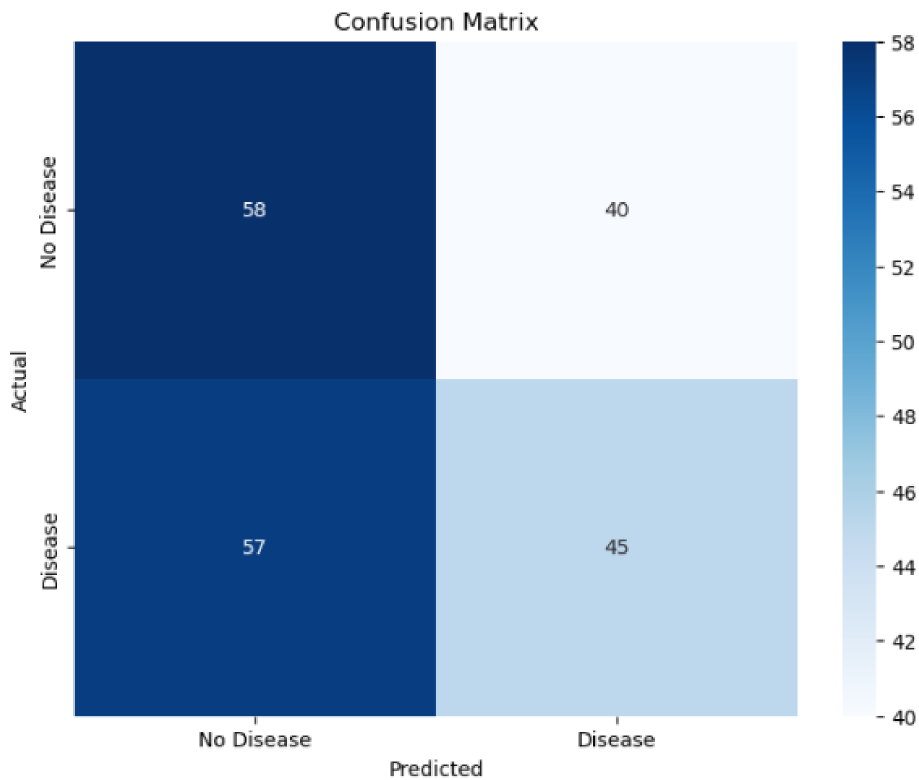
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
np.random.seed(42)  # For reproducibility
num_samples = 1000
age = np.random.randint(30, 80, num_samples)
sex = np.random.randint(0, 2, num_samples)
cp = np.random.randint(0, 4, num_samples)
trestbps = np.random.randint(90, 200, num_samples)
chol = np.random.randint(150, 300, num_samples)
fbs = np.random.randint(0, 2, num_samples)
restecg = np.random.randint(0, 2, num_samples)
thalach = np.random.randint(60, 200, num_samples)
exang = np.random.randint(0, 2, num_samples)
oldpeak = np.random.uniform(0, 6, num_samples)
slope = np.random.randint(0, 3, num_samples)
ca = np.random.randint(0, 4, num_samples)
thal = np.random.randint(1, 4, num_samples)
target = np.random.randint(0, 2, num_samples)
data = pd.DataFrame({
'age': age, 'sex': sex, 'cp': cp,
'trestbps': trestbps, 'chol': chol,
'fbs': fbs, 'restecg': restecg, 'thalach': thalach, 'exang': exang,
'oldpeak': oldpeak, 'slope': slope, 'ca': ca,
'thal': thal, 'target': target})
X = data.drop('target', axis=1)
y = data['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(class_report)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Disease', 'Disease'], yticklabels=['No Disease', 'Disease'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
importance = model.coef_[0]
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance': importance})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
plt.title('Feature Importance')
plt.xlabel('Coefficient Value')
plt.ylabel('Features')
plt.axvline(0, color='red', linestyle='--')  # Adding a vertical line at 0
plt.show()
```

OUTPUT:

```
Accuracy: 0.52
Confusion Matrix:
[[58 40]
 [57 45]]
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.59      0.54        98
           1       0.53      0.44      0.48       102

    accuracy                           0.52       200
   macro avg       0.52      0.52      0.51       200
weighted avg       0.52      0.52      0.51       200
```



RESULT:

Thus, the program for heart disease prediction is executed successfully.

10. BREAST CANCER DIAGNOSIS

EX.N0 : 10	**Breast Cancer Diagnosis**
DATE : 09/10/2024	

PROBLEM STATEMENT: Classify tumors as benign or malignant based on features.

PYTHON CONCEPTS: Classes, sequences.

VISUALIZATION: Confusion matrix, bar plots.

MULTIVARIATE ANALYSIS: LDA, logistic regression.

DATASET: Breast Cancer Wisconsin Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

PROGRAM:

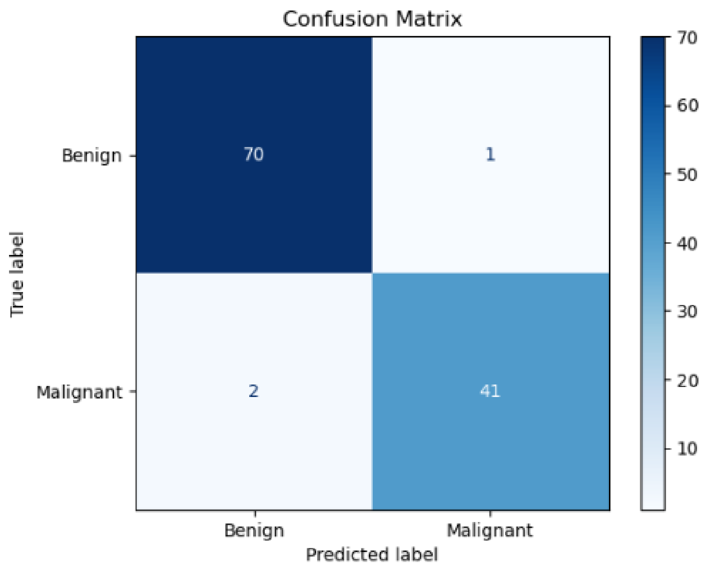
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
np.random.seed(42)  # For reproducibility
num_samples = 1000
age = np.random.randint(30, 80, num_samples)
sex = np.random.randint(0, 2, num_samples)
cp = np.random.randint(0, 4, num_samples)
trestbps = np.random.randint(90, 200, num_samples)
chol = np.random.randint(150, 300, num_samples)
fbs = np.random.randint(0, 2, num_samples)
restecg = np.random.randint(0, 2, num_samples)
thalach = np.random.randint(60, 200, num_samples)
exang = np.random.randint(0, 2, num_samples)
oldpeak = np.random.uniform(0, 6, num_samples)
slope = np.random.randint(0, 3, num_samples)
ca = np.random.randint(0, 4, num_samples)
thal = np.random.randint(1, 4, num_samples)
target = np.random.randint(0, 2, num_samples)
data = pd.DataFrame({
'age': age, 'sex': sex, 'cp': cp,
'trestbps': trestbps, 'chol': chol,
'fbs': fbs, 'restecg': restecg, 'thalach': thalach, 'exang': exang,
'oldpeak': oldpeak, 'slope': slope, 'ca': ca,
'thal': thal, 'target': target})
X = data.drop('target', axis=1)
y = data['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(class_report)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Disease',
'Disease'], yticklabels=['No Disease', 'Disease'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
importance = model.coef_[0]
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance': importance})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
plt.title('Feature Importance')
plt.xlabel('Coefficient Value')
plt.ylabel('Features')
plt.axvline(0, color='red', linestyle='--')  # Adding a vertical line at 0
plt.show()
```

OUTPUT:

```
              precision    recall  f1-score   support

           0       0.97      0.99      0.98        71
           1       0.98      0.95      0.96        43

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```




```
Enter the following features for prediction:
radius_mean:  14.5
texture_mean:  20.0
perimeter_mean:  90.0
area_mean:  560.0
smoothness_mean:  0.1
compactness_mean:  0.15
concavity_mean:  0.2
concave points_mean:  0.1
symmetry_mean:  0.18
fractal_dimension_mean:  0.06
radius_se:  0.6
texture_se:  1.2
perimeter_se:  10.0
area_se:  40.0
smoothness_se:  0.007
compactness_se:  0.03
concavity_se:  0.03
concave points_se:  0.02
symmetry_se:  0.02
fractal_dimension_se:  0.003
radius_worst:  16.0
texture_worst:  25.0
perimeter_worst:  100.0
area_worst:  800.0
smoothness_worst:  0.14
compactness_worst:  0.25
concavity_worst:  0.3
concave points_worst:  0.15
symmetry_worst:  0.25
fractal_dimension_worst:  0.08
The tumor is predicted to be: Malignant
Based on the symptoms provided, the person may be at risk.
```

RESULT:

Thus, the program for breast cancer diagnosis is executed successfully.

11. PREDICTING FLIGHT DELAYS

EX.N0 : 11	PREDICTING FLIGHT DELAYS
DATE : 16/10/2024	

PROBLEM STATEMENT: Predict flight delays based on historical data.

PYTHON CONCEPTS: File reading/writing, functions.

VISUALIZATION: Line plots, scatter plots.

MULTIVARIATE ANALYSIS: Regression, clustering.

DATASET: Flight Delay Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

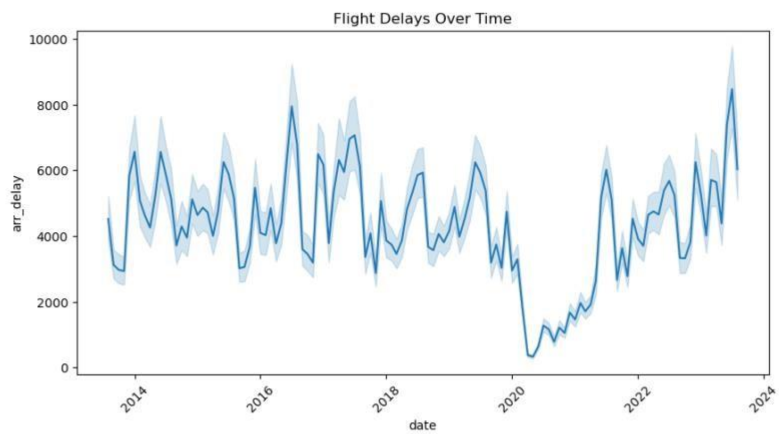
PROGRAM:

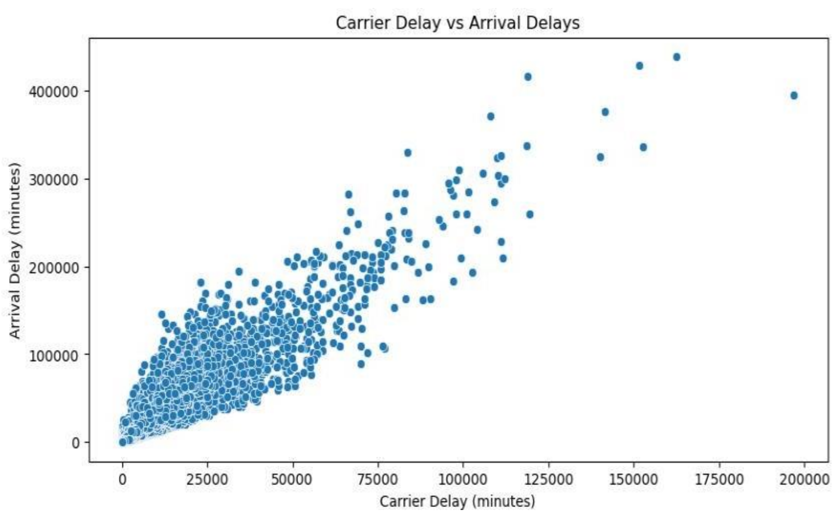
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
df = pd.read_csv('C:/Users/APPU/Downloads/Airline_Delay_Cause.csv')
print(df.columns)
print(df.isnull().sum())
df.dropna(inplace=True)  # or df.fillna(method='ffill', inplace=True)
if 'year' in df.columns and 'month' in df.columns:
df['date'] = pd.to_datetime(df[['year', 'month']].assign(day=1))
plt.figure(figsize=(10, 5))
sns.lineplot(data=df, x='date', y='arr_delay')  # Adjust if necessary
plt.title('Flight Delays Over Time')
plt.xticks(rotation=45)
plt.show()
delay_column = 'arr_delay'  # Using 'arr_delay' for now
if 'carrier_delay' in df.columns and delay_column in df.columns:
plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='carrier_delay', y=delay_column)  # Adjust as needed
plt.title('Carrier Delay vs Arrival Delays') plt.xlabel('Carrier Delay (minutes)')
plt.ylabel('Arrival Delay (minutes)') plt.show()
else: print("Check the delay columns: 'carrier_delay' or 'arr_delay' do not exist in the
DataFrame.")
df['day_of_week'] = df['date'].dt.dayofweek # Monday=0, Sunday=6
features = ['day_of_week', 'arr_flights', 'carrier_ct']  # Modify as needed
X = df[features] y = df[delay_column]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
print('Mean Absolute Error:', mean_absolute_error(y_test, predictions))
print('Mean Squared Error:', mean_squared_error(y_test, predictions))
print('R-squared:', r2_score(y_test, predictions))
plt.figure(figsize=(10, 5)) plt.scatter(y_test, predictions)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2)  # Line
of equality
plt.title('Predictions vs Actual Delays') plt.xlabel('Actual Delays')
plt.ylabel('Predicted Delays') plt.show()
```

OUTPUT:

```
Index(['year', 'month', 'carrier', 'carrier_name', 'airport', 'airport_name',
       'arr_flights', 'arr_del15', 'carrier_ct', 'weather_ct', 'nas_ct',
       'security_ct', 'late_aircraft_ct', 'arr_cancelled', 'arr_diverted',
       'arr_delay', 'carrier_delay', 'weather_delay', 'nas_delay',
       'security_delay', 'late_aircraft_delay'],
      dtype='object')
year                     0
month                    0
carrier                  0
carrier_name             0
airport                  0
airport_name             0
arr_flights            240
arr_del15              443
carrier_ct             240
weather_ct             240
nas_ct                 240
security_ct            240
late_aircraft_ct       240
arr_cancelled          240
arr_diverted           240
arr_delay              240
carrier_delay          240
weather_delay          240
nas_delay              240
security_delay         240
late_aircraft_delay    240
dtype: int64
```






```
Mean Absolute Error: 1592.2201262853362
Mean Squared Error: 25524907.35571326
R-squared: 0.8439698040165798
```

RESULT:

Thus, the program for predicting flight delays is executed successfully.

12. ENERGY CONSUMPTION FORECASTING

EX.N0 : 12	**ENERGY CONSUMPTION FORECASTING**
DATE : 23/10/2024	

PROBLEM STATEMENT: Forecast energy consumption based on historical data.

PYTHON CONCEPTS: Functions, numeric types.

VISUALIZATION: Line plots, heatmaps.

MULTIVARIATE ANALYSIS: Time series analysis, regression.

DATASET: Energy Consumption Dataset

ALGORITHM:

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

PROGRAM:

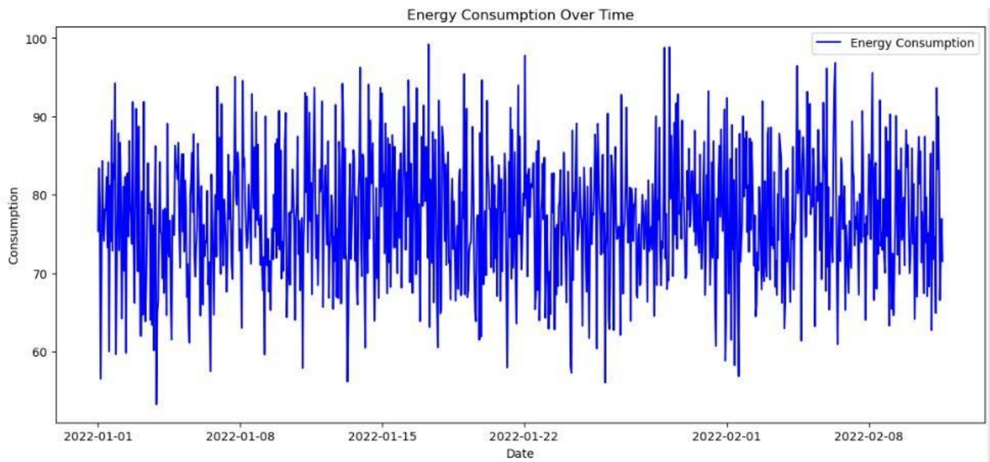
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
data = pd.read_csv('C:/Users/APPU/Downloads/energy_consumption_dataset.csv',
parse_dates=['Timestamp'], index_col='Timestamp')
print(data.head()) print(data.info())
```

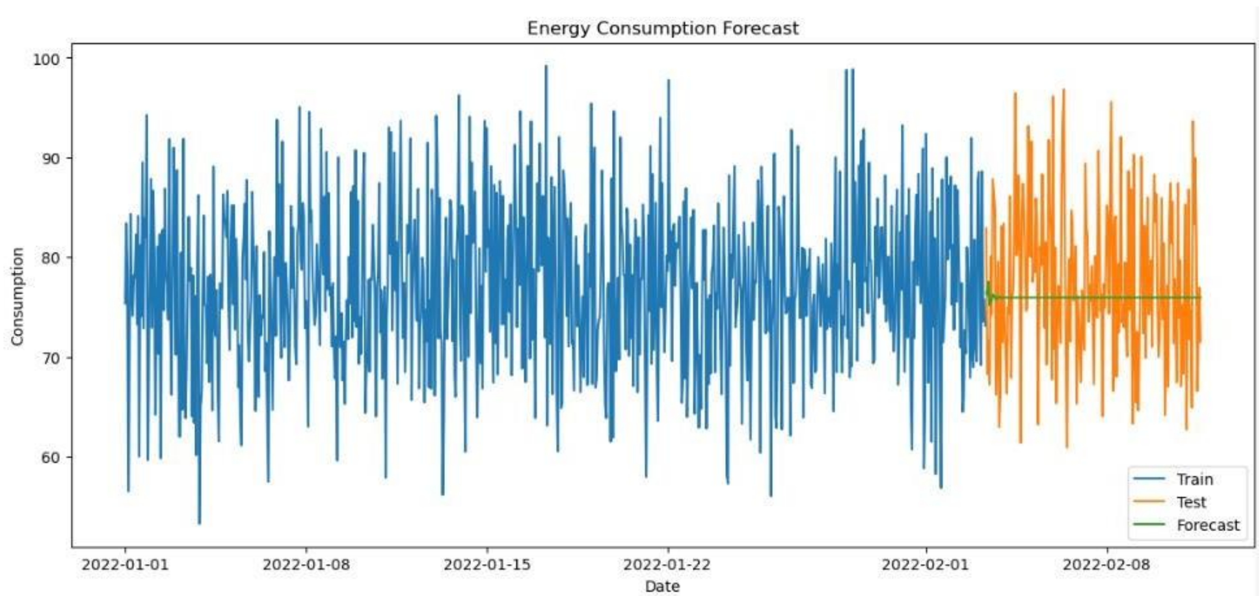
```
data = data.fillna(method='ffill')
plt.figure(figsize=(14, 6))
plt.plot(data['EnergyConsumption'], color='blue', label='Energy Consumption')
plt.title('Energy Consumption Over Time')
plt.xlabel('Date') plt.ylabel('Consumption')
plt.legend() plt.show()
numeric_data = data.select_dtypes(include=[np.number])
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix') plt.show()
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(data['EnergyConsumption'], model='additive', period=24)  # Adjust
period based on your data's frequency
result.plot() plt.show()
train_size = int(len(data) * 0.8)
train, test = data['EnergyConsumption'][:train_size], data['EnergyConsumption'][train_size:]
model = ARIMA(train, order=(5, 1, 0)) # Adjust (p,d,q) based on your data's behavior
fitted_model = model.fit()
forecast = fitted_model.forecast(steps=len(test))
forecast_index = test.index
mse = mean_squared_error(test, forecast)
rmse = np.sqrt(mse)
print(f'RMSE: {rmse}')
plt.figure(figsize=(14, 6))
plt.plot(train, label='Train')
plt.plot(test, label='Test')
plt.plot(forecast_index, forecast, label='Forecast')
plt.title('Energy Consumption Forecast')
plt.xlabel('Date')
plt.ylabel('Consumption')
plt.legend()
plt.show()
```

OUTPUT:

Timestamp	Temperature	Humidity	SquareFootage	Occupancy \
2022-01-01 00:00:00	25.139433	43.431581	1565.693999	5
2022-01-01 01:00:00	27.731651	54.225919	1411.064918	1
2022-01-01 02:00:00	28.704277	58.907658	1755.715009	2
2022-01-01 03:00:00	20.080469	50.371637	1452.316318	1
2022-01-01 04:00:00	23.097359	51.401421	1094.130359	9

Timestamp	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek
2022-01-01 00:00:00	On	Off	2.774699	Monday
2022-01-01 01:00:00	On	On	21.831384	Saturday
2022-01-01 02:00:00	Off	Off	6.764672	Sunday
2022-01-01 03:00:00	Off	On	8.623447	Wednesday
2022-01-01 04:00:00	On	Off	3.071969	Friday





RESULT:

Thus, the program for energy consumption forecasting is executed successfully.